

3#MoSummit2016





The Innovation Imperative



2016 Director's Regulatory Summit

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Panelists

Brent Kabler, PhD, Missouri DIFP Ashley Ramos, Merlinos and Associates, Inc. Kelsey Brunette, Munich Re

Moderated by: Angela Nelson, Missouri DIFP





Is Data Mining a Valid Statistical Method? OR The value of the p-value and the

significance of significance

Brent Kabler, PhD





Overview

Introduce a few statistical concepts

Causality, spurious relationships, and random relationships

P-value and statistical significance

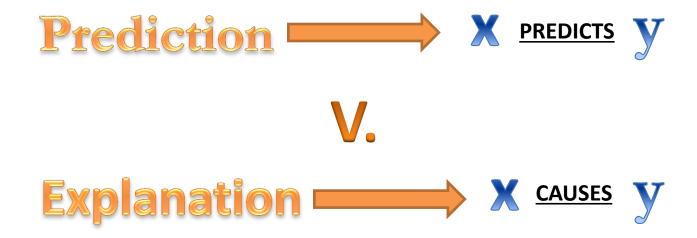
Big data, data mining and *post hoc* analysis – Departures from the scientific method (or hypothetico-deductive method).

Recent warning by the American Statistical Association regarding the pitfalls of data mining and misuses of the concept of statistical significance.





Uses of Statistics



While almost the entirety of the natural and social sciences are concerned virtually exclusively with **explanation**, the purpose of insurance rate-making is **prediction**.





ASOP on Causality

- "While the actuary should select risk characteristics that are related to expected outcomes, it is not necessary for the actuary to establish a cause and effect relationship between the risk characteristic and expected outcome in order to use a specific risk characteristic"
 - Actuarial Standard of Practice No. 12, Section 3.2.2

(emphasis added)

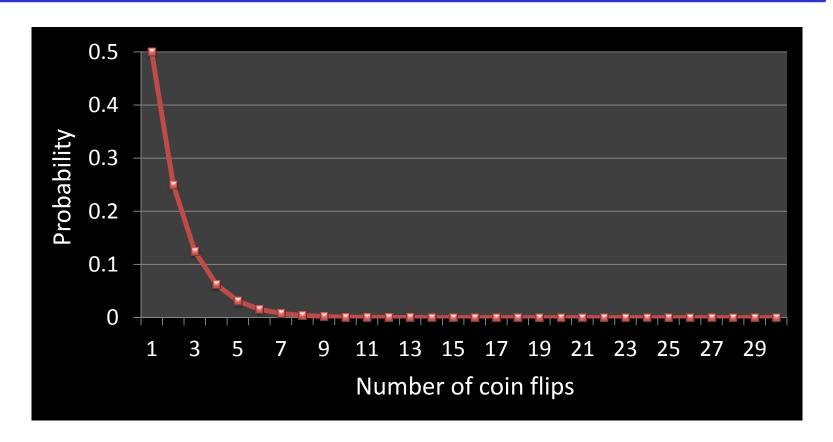
Translation: It is only necessary to ascertain that a relationship exists; it is **NOT NECESSARY** to **UNDERSTAND** the relationship.





P-values & Statistical Significance

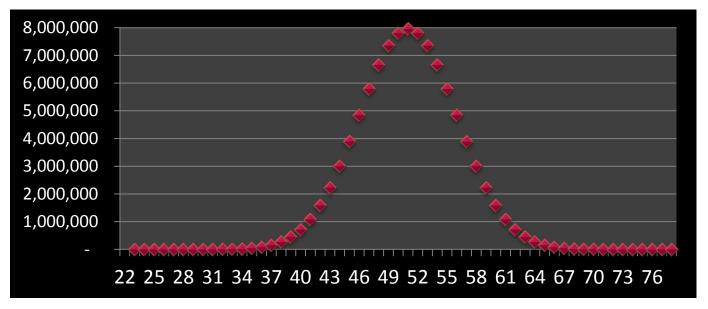
Probability of obtaining all "heads" from x flips of a fair coin.







100 million virtual trials of a flip of 100 coins



Highest Number of Heads Obtained	Trial when observed
77	75,400,000
77	88,300,000
77	89,400,000
78	3,530,000
80	38,100,000



Actual probability of obtaining 100 heads in 100 flips of a coin

Probability 100 heads = $(1/2)^{100}$

Or

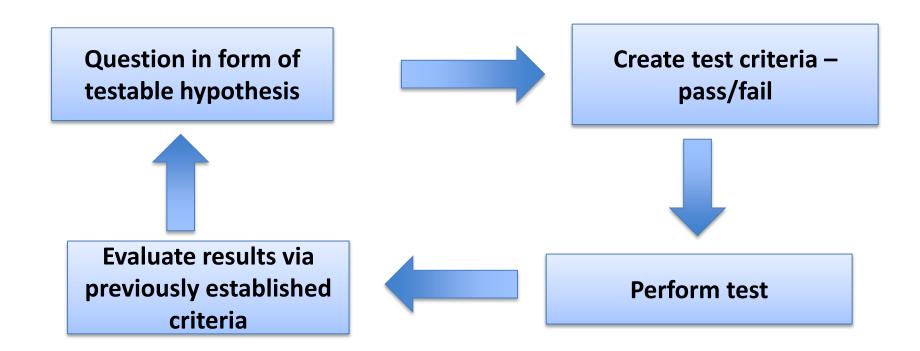
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1,267,650,600,288,299,401,496,703,205,376



Uses & Misuses of P-values

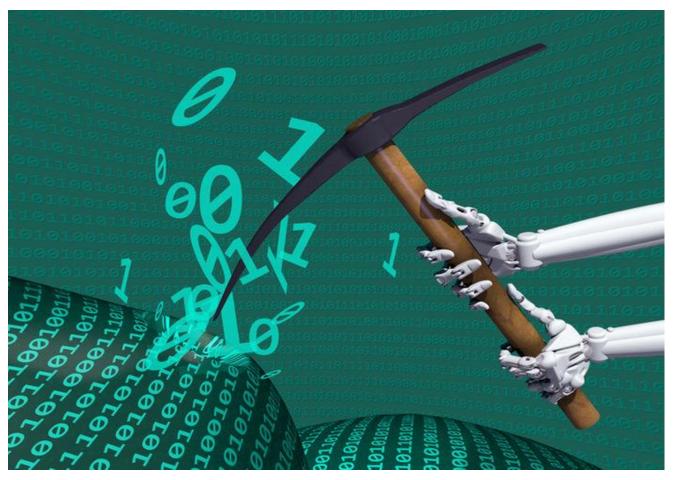
Hypothetico-Deductive Method







Data mining – (often) random search for patterns & correlations







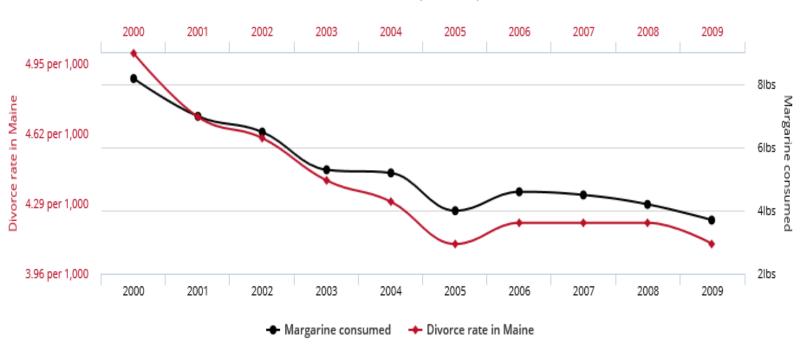
Random(?) Correlations

Divorce rate in Maine

correlates with

Per capita consumption of margarine

Correlation: 99.26% (r=0.992558)



tylervigen.com

Source: http://www.tylervigen.com/spurious-correlations



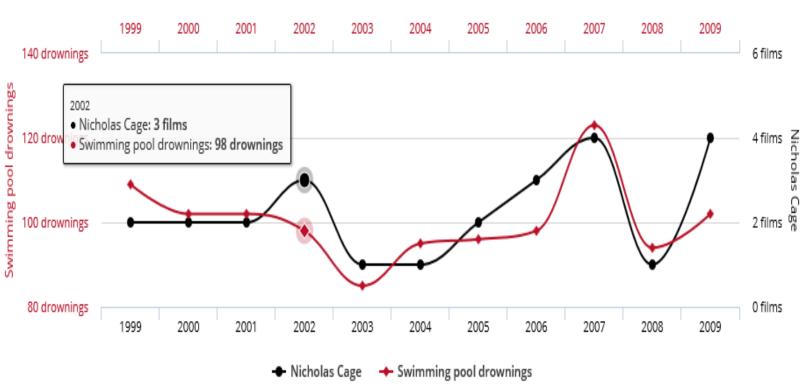
Number of people who drowned by falling into a pool

≣

correlates with

Films Nicolas Cage appeared in

Correlation: 66.6% (r=0.666004)



tylervigen.com





Literal Dead-Ends

Aspirin therapy more likely to result in death than recovery for:

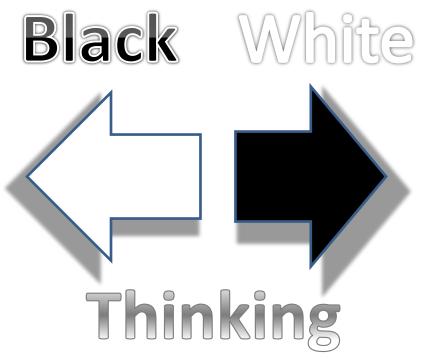


Findings of a recent international study of survivors of heart attack, involving more than 134,000 patients in over 20 countries.





Analytical Dead Ends: A Study in...



Nosek, Brian A., Jeffrey R. Spies, and Matt Motyl. 2012. Scientific Utopia: II. Restructuring incentives and practices to promote truth over publishability. **Perspectives on Psychological Science.** 7(6): 615-631





Post-Hoc Hypothesis Testing

Looking for hidden meanings in text...and finding them.



"Equidistant letter sequences in the book of Genesis." (Statistical Science, Vol. 9 (1994) 429-438.)



Regulation occurs in the absence of checks considered essential in science

- 1. Double-blind peer review process
- 2. Complete transparency
- 3. Access to research materials and data
- 4. Replication





Statement by the American Statistical Association

Scientific conclusions **should not be based only** on whether a p-value passes a specified threshold.

"Researchers should bring many contextual factors into play to derive scientific inferences, including the design of the study, the quality of the measurements, the external evidence for the phenomenon under study [i.e. causal or theoretical knowledge], and the validity of the assumptions that underlie the data analysis" (page 9).





Statement by the American Statistical Association

Proper inference requires full reporting and transparency.

"Cherry-picking promising findings, also known by such terms as data dredging, significance chasing...and 'p-hacking,' leads to a spurious excess of statistically significant results...and should be vigorously avoided."

"Researchers should disclose the number of hypotheses explored during the study, all data collection decisions, all statistical analyses conducted and all p-values computed."





Implications for insurance regulation?





PREDICTIVE MODELS AND INSURANCE:

A REGULATOR'S PERSPECTIVE

Ashley P. Ramos, FCAS, MAAA

Merlinos & Associates



Director's Regulatory Summit 2016 The Innovation Imperative October 13, 2016

AGENDA

- What are Predictive Models?
- Why use Predictive Models in Insurance?
- Regulatory Concerns and Challenges



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WHAT IS A MODEL?

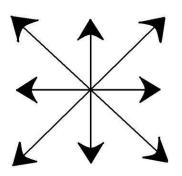
A description of a system using mathematical concepts and language.



WHAT IS A MODEL?

- Traditional ratemaking methods use one-way analysis.
- One-way analysis looks at the direct relationship one rating factor has in isolation, such as gender, on expected loss costs.

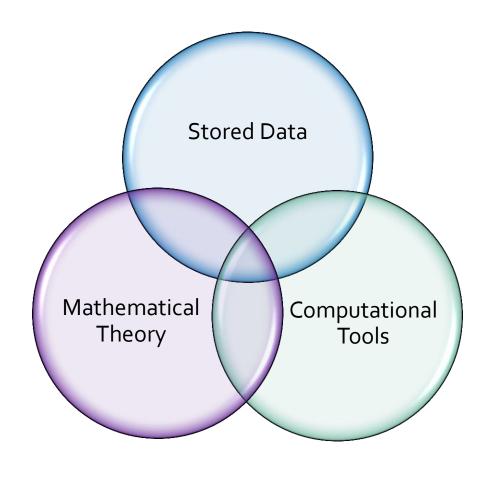






PREDICTIVE MODELING

The process of creating, testing, and validating a model to best predict the probability of an outcome.





AN EXAMPLE: GENERALIZED LINEAR MODELS



- GLMs are one of the most common types of predictive modeling.
- Unlike traditional oneway analysis, GLMs can consider the impacts of many rating factors simultaneously.



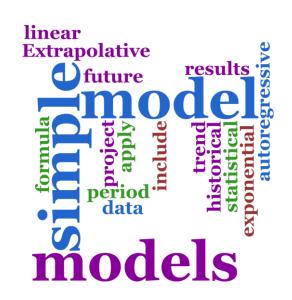
AGENDA

- What are Predictive Models?
- Why use Predictive Models in Insurance?
- Regulatory Concerns and Challenges



WHY USE MODELS IN INSURANCE?

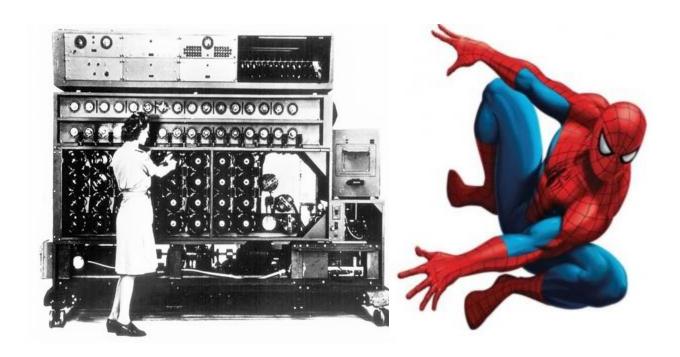
- Minimize human errors and biases when interpreting complex data
- Ensure consistency in decision making and application of results





WHY USE MODELS IN INSURANCE?

Better Data + More Computing Power = Increased Predictive Accuracy





AGENDA

- What are Predictive Models?
- Why use Predictive Models in Insurance?
- Regulatory Concerns and Challenges



REGULATORY CONCERNS

Excerpt from RSMO 379.318:

Rates shall not be excessive, inadequate, or unfairly discriminatory....

Unfair discrimination shall be defined to include, but shall not be limited to, the use of rates which unfairly discriminate between risks having essentially the same hazard.



REGULATORY CONCERNS

Excerpt from RSMO 379.318:

Risks may be grouped by classifications... or other reasonable methods....

Such standards may measure any differences among risks that can be demonstrated to have a probable effect upon losses or expenses.



TRANSPARENCY CONCERNS

Can the regulator:

- See how the model works?
- Be assured that the information will be used consistently and uniformly?
- •Understand the information obtained and how it is used?
- •Recreate someone's rate from the filed manual?



CHALLENGES REVIEWING PREDICTIVE MODELS

Increased use of 3rd party data and non-traditional variables.

Changing rapidly as machine learning advances and improves.

Gaps between statistical findings and common sense.



CHALLENGES REVIEWING PREDICTIVE MODELS

A model should:

- Demonstrate predictability
- Predict behavior better than the current model
- Be built with adequate testing and validation
- Comply with state regulations



EASING THE REVIEW PROCESS

- Regulators have to review lots of models...Be helpful!
- Many filings focus on statistical detail only...don't neglect to tell the story of the modeling process.
- Demonstrating a well thought out and controlled modeling process can be more important than a hard statistic
- Step back from numbers, and ask:
 - ✓ Do the variables make sense?
 - ✓ How is management using my model? Is that appropriate?
 - ✓ If I was a regulator, might I have a concern with this?



PREDICTIVE MODELS **AND INSURANCE:**

A REGULATOR'S **PERSPECTIVE** Thank you:

Ashley P. Ramos, FCAS, MAAA

Merlinos & Associates



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Autonomous Vehicles Director's Regulatory Summit

October 13, 2016 Kelsey Brunette – Ideation Analyst Munich Reinsurance America, Inc.



Agenda



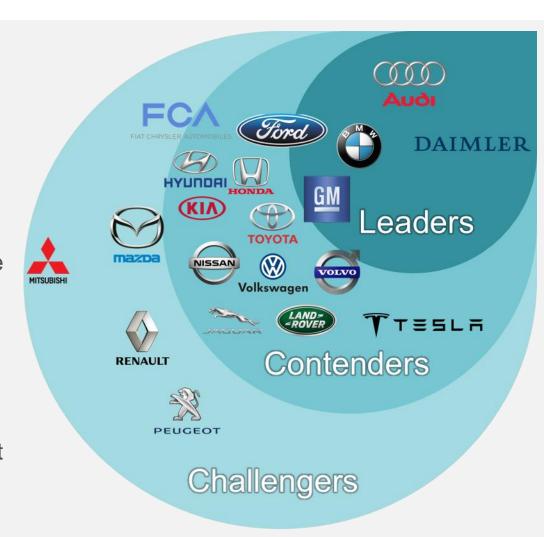
1. AV 101

- Who is making autonomous vehicles?
- What are autonomous vehicles?
- Why should we encourage autonomous vehicles?
- How are autonomous vehicles being deployed?
- 2. Tech
- 3. Regulation
- 4. Underwriting
- 5. Impact

Who - OEMs



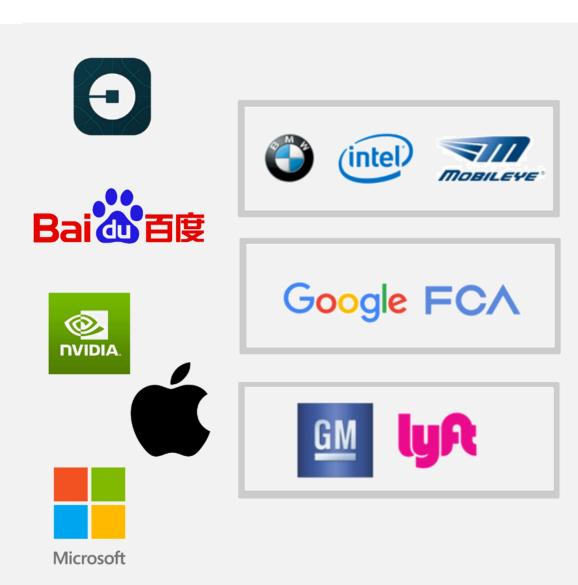
- Original equipment
 manufacturers (OEMs) used to
 focus on semi-autonomous
 capabilities (ADAS systems)
- GM, Ford, and other OEMs have made key partnerships and invested heavily in acquiring talent
- OEMs are participating in lobbying and policy development



Who – Tech Companies



Whether looking to manufacture cars or just write software, partnerships with tech giants is a key factor in the future of AV development



Who – Startups



AVs are not only for the Fortune 500



















Auro Robotics





Driverless, Highly-Automated Vehicle (HAV) , Autonomous, Self-Driving					
Autonomous	Semi-Autonomous Advanced Driver Systems (ADAS) Tech that takes over some of the responsibilities of driving. Examples include automatic braking, lane keeping and adaptive cruise control.				
	Autonomous Vehicle Tech that takes over all the responsibilities of driving. Examples include the Google Car project and low speed autonomous shuttles.				
Connected	V2X Technology (Connected Vehicles) Tech that allows devices to speak to each other. Examples include cars talking to each other, or cars talking to stop lights.				

What – Autonomous Vehicle Levels



Rejected	Adopted
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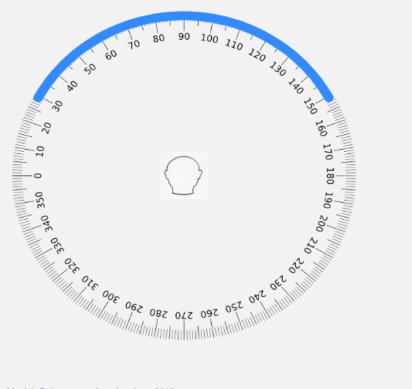
National Highway Transportation and Safety Administration NHTSA		Society of Automotive Engineers SAE	
0	No autonomy	0	No autonomy
1	Vehicle takes over one aspect of driving, ex: adaptive cruise control	1	Driver assistance program controls either steering or acceleration
2	Vehicle combine two or more level 1 systems, ex: ACC with lane centering	2	Driver assistance controls both steering and acceleration
3	Driver is expected to retain occasional control	3	Automated system controls, human driver expected to intervene
4	Vehicle controls operation from origin to destination	4	Automated system controls, human drive not expected to intervene
		5	Automated system controls under all roadway and environmental conditions

Why – Humans vs Machines



Humans

Field of view: ~120 degrees Distance: 30 meters ahead



Autonomous Vehicles

Field of view: 360 degrees Distance: 300 meters ahead

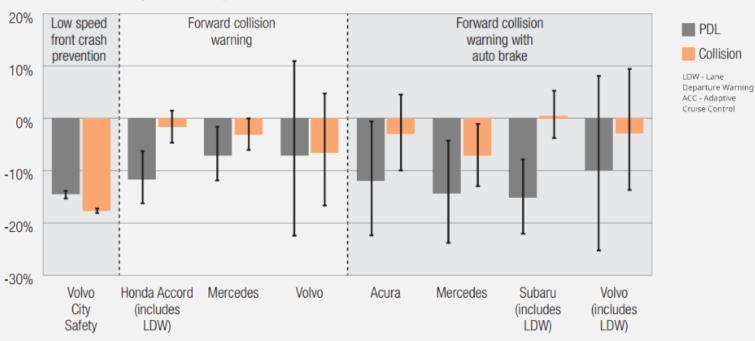


Why – Automation Makes a Difference



- According to NHTSA, roughly 90% of accidents are caused by human error
- By reducing driver error, AV technology is predicted to significantly reduce the number of motor vehicle accidents

Figure 1: Changes in physical damage claim frequency for front crash prevention systems



Why – NHTSA's Call to Action

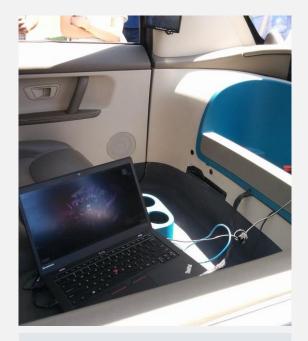


- In 2015, vehicle miles traveled (VMT) increased 3.5% over 2014, the largest increase in nearly 25 years.
- There were 35,092 fatalities as a result of vehicle crashes in 2015, ending a
 5-decade trend of declining fatalities with a 7.2% increase in deaths from 2014.
- The last single-year increase of this magnitude was in 1966, when fatalities rose
 8.1% from the previous year.

US Department of Transportation (DOT), NHTSA, and the White House are issuing an **unprecedented call to action** to involve a wide range of stakeholders in helping determine the causes of the increase.

How – Differences in Philosophy

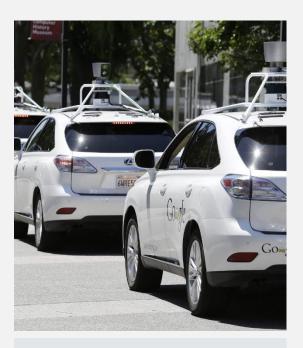




- Steering wheel or no steering wheel?
- Some believe that people will never be able to successfully take back control of steering



- Fully mapped or deep machine learning?
- Some AV teams try to cover every situation, others are teaching the machine to think for itself



- Direct to consumers or commercial?
- Manufacturers are now focusing on releasing vehicles as fleets

How – Rate of Adoption





Tech – The Basics



Sensors

Ex: blind spot detection

Cameras

Ex: lane keeping and sign reading

Radar

 Ex: measuring distance between cars for adaptive cruise control

LiDAR

- Light Detection and Ranging
- 8 to 60 lasers pointing in every direction

Processor

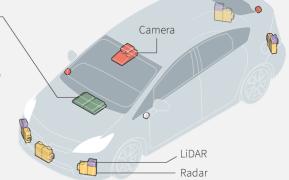
How self-driving cars see the road

Autonomous vehicles rely on a host of sensors to plot their trajectory and avoid accidents.

• Multi-domain controller

Manages inputs from camera, radar, and LiDAR.

With mapping and navigation data, it can confirm decisions in multiple ways.







Source: Delphi



• Radar
Radio waves are
sent out and
bounced off objects.
Can work in all
weather but cannot
differentiate objects.

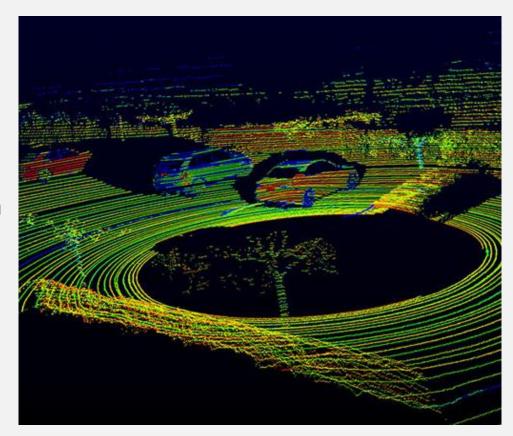


• LiDAR
Light pulses are
sent out and
reflected off objects.
Can define lines on
the road and works
in the dark.

Tech – LiDAR

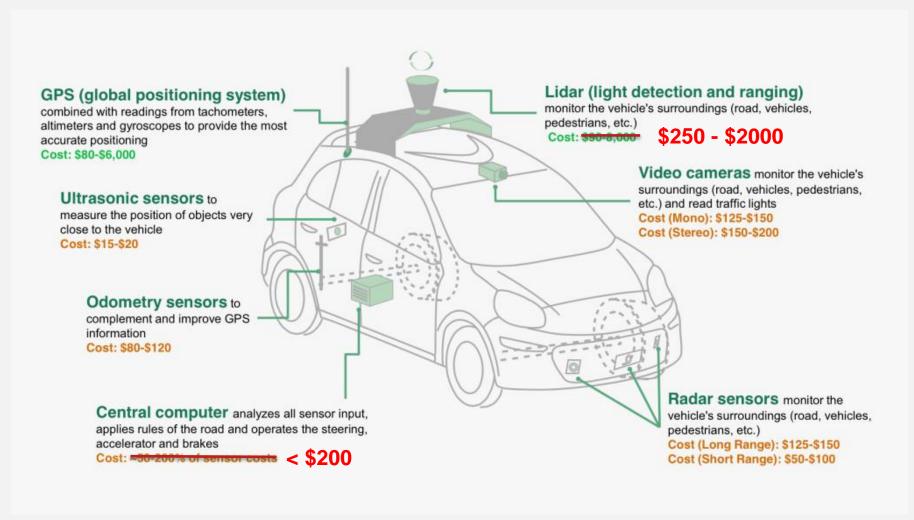


- Laser based detectors that generate 300,000 to 2,200,0000 data points per second
- LiDAR systems range from having 8 to 60 lasers spinning in all directions to complete highresolution, 3D data
- Leading manufacturer Velodyne received \$150 million investment from Ford and Baidu



Tech – Costs of Technology





Source: BCG, Revolution in the Driver's Seat: The Road to Autonomous Vehicles, 4/21/15; Spectrum, Israeli Startup Innoviz Promises \$100 Solid-State Automotive Lidar by 2018, 9/9/16; Fortune, Nvidia Shows Off New AI Computer for Baidu's Self-Driving Car, 9/13/16, Image credit: Wired, Turns Out the Hardware in Self-Driving Cars is Pretty Cheap, 4/22/16

Tech – Overview of Timeline



Manufacturer	Target Year	Target Achievement	Announcement Date
Tesla	Q4 2017	Level 4 better than human	12/21/15
NuTonomy	2018	Driverless taxis	5/24/16
Delphi/Mobileye	2019	Off the shelf level 4 system	8/23/16
Baidu	2021	Mass produce level 4	6/2/16
Ford	2021	Mass produce for ridesharing	8/16/16
BMW	2021	Self-driving electric vehicle	5/12/16
Ford	2025	Mass produce for consumer	8/12/16

Source: Electrek, Elon Musk On Tesla Fully Autonomous Car: 'What We've Got Will Blow People's Minds, It Blows My Mind . . . It'll Come Sooner Than People Think', 8/3/16; Wsj, Self-driving Car Startup Nutonomy Raises \$16 Million In Funding, 5/24/16; The Verge, Delphi and Mobileye are Teaming Up to Build A Self-driving System By 2019, 8/23/16; Wsj, Baidu Plans to Mass Produce Autonomous Cars In Five Years, 6/2/16; Reuters, Ford Plans Self-driving Car For Ride Share Fleets In 2021, 8/16/16; Electrek, Bmw will Launch the Electric and Autonomous Inext In 2021, New I8 In 2018 and Not Much Inbetween, 5/12/16

Regulation – New Federal Policy



- Federal Model Policy released 9/20/16
- The DOT and NHTSA have released an extensive document highlighting policy to cover the next year for:
 - How DOT will regulate using current tools
 - How DOT hopes to regulate using new tools



"We do not intend to write the final word on highly automated vehicles here. Rather, we intend to establish a foundation and a framework upon which future Agency action will occur."

Regulation – What This Means for Insurance



- The DOT has tasked state departments have been tasked by the DOT to proactively address liability
- The DOT stated they are likely to form a commission to advise the state departments on specific issues
- The committees formed by states to address all AV issues are advised to have state DOI participation



2017 will have more legislative movement regarding AVs that address deeper and more complex issues than whether or not the state will allow AV testing

Underwriting - Shifts in Liabilities and Premiums



Auto liability



Likely to shrink

Cyber risk tech E&O/IoT



Likely to increase

Products liability



Likely to increase

Transition to full vehicle autonomy

Varying degrees of impact over time

Auto physical damage



Likely no material change

Equipment breakdown/warranty



Likely to increase

Product recall



Likely to increase

Impact – Other Industries



- OEM'S
- HOSPITALS
- FIRST RESPONDERS
- TELECOMMUNICATIONS
- URBAN PLANNERS
- MASS TRANSIT MANUFACTURERS AND OPERATORS
- ELECTRIC GRID
- CONSUMER ELECTRONICS
- PERCEPTION SYSTEMS
- MATERIALS SCIENCE
- NON-FOSSIL FUEL PROVIDERS
- COAL INDUSTRY

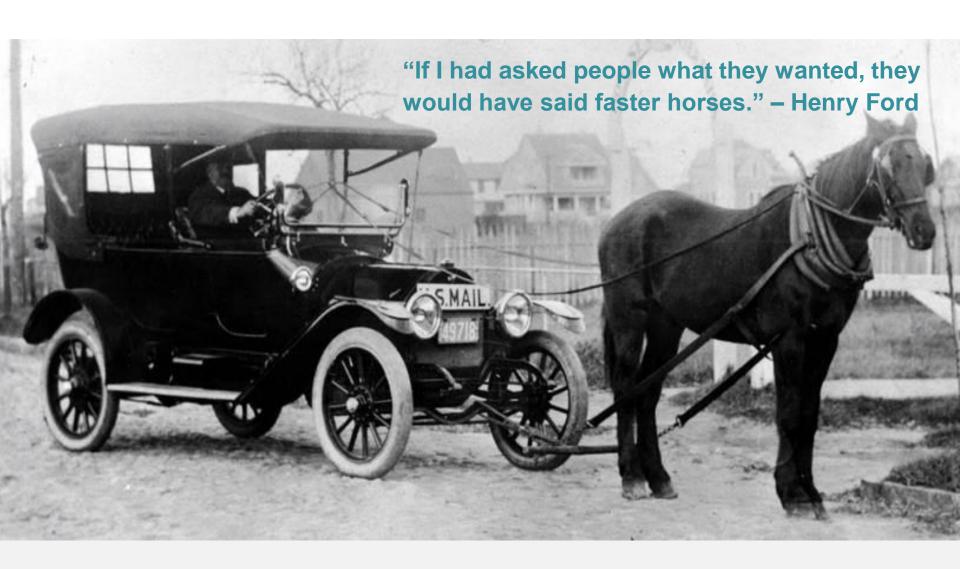
- OIL COMPANIES
- TOURISM UNIONS
- CHIROPRACTIC
- TORT & LIABILITY RELATED LEGAL FIELDS
- TRANSPORTATION REGULATORS
- CRASH TESTING FACILITIES
- DRIVER EDUCATION
- TRUCKING AND FREIGHT
- PARKING LOT OPERATORS
- VENTURE CAPITAL
- VEHICLE FINANCING/LEASING
- MINING

- TRANSPORTATION MONITORING
- BIKE MANUFACTURERS
- RESEARCH UNIVERSITIES
- ENGINEERING PROGRAMS
- AUTO REPAIR FACILITIES
- TRAFFIC INFRASTRUCTURE
- PERSONAL AND COMMERCIAL INSURANCE
- STOCK AND BOND EXCHANGES
- TIRE INDUSTRY
- HUMAN MACHINE INTERFACE

- ARTIFICIAL INTELLIGENCE
- MILITARY
- SOFTWARE DEVELOPERS
- CLOUD COMPUTING
- MOBILE DEVICE MANUFACTURERS
- VEHICLE SALVAGE OPERATIONS
- CUSTOMS AND BORDER PATROL
- AUTO CLAIM LITIGATION
- VEHICLE SUPPLIERS (TIER 1& 2)
- USED VEHICLE DEALERSHIPS

Impact - Risk or Opportunity?







Thank you for your attention.

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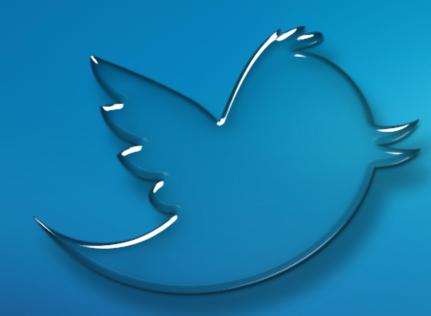




Any questions







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